Electricity Supply Interruptions: Sectoral Interdependencies and the Cost of Energy Not Served for the Scottish Economy

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Abstract

The power sector has a central role in modern economies and other infrastructures rely heavily upon secure electricity supplies. Due to interdependencies, major electricity supply interruptions result in cascading effects in other sectors of the economy. This paper investigates the economic effects of large power supply disruptions taking such interdependencies into account. We apply a dynamic inoperability input–output model (DIIM) to 101 sectors (including the households) of the Scottish economy in 2009 in order to explore direct, indirect, and induced effects of electricity supply interruptions. We then estimate the societal cost of energy not supplied (SCENS) due to a power interruption, in the presence of interdependency among the sectors. The results show that the most economically affected industries, following an outage, can be different from the most inoperable ones. The results also indicate that SCENS varies with duration of a power cut, ranging from around £4,300/MWh for a one-minute outage to around £8,100/MWh for a three hour (and higher) interruption. The economic impact of estimates can be used to design policies for contingency measures and preventive investments in the power sector.

Keywords: Power blackout, inoperability input–output model, interdependent economic systems, cost of energy not supplied

JEL classifications: C67, L52, Q40

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1. Introduction

Modern economies are crucially and increasingly dependent on reliable energy services from the power sector. This dependence, to a large extent, stems from the reliance of other critical infrastructure (CI) sectors such as natural gas, water supplies, petroleum, telecommunications, and transportation, on power supplies. Meanwhile, critical infrastructures are also interdependent and interact with each other in numerous and sometimes complex ways.

The interdependencies among the CIs are the main factor behind the unforeseen chains of events, or the ‘cascade effects’, in the event that a CI fails. This is particularly important in the case of failure in the power supply system, as this tends to propagate the ripple rapidly to other infrastructure sectors. Furthermore, the ripple effects of electricity supply shocks often reach beyond their first-order effects. This implies that the socio-economic cost of power outages can be larger when the cascading effects and interdependencies among infrastructure industries are taken into account (Kjølle et al., 2012).

Previous experience from exceptional events in the power sector has raised the concerns about the economic consequences of such failures.[2] An important part of these costs is due to the indirect and induced effects due to sectoral interdependencies and the spilling over of power failures to other infrastructures.[3] Despite its importance, the information available about the economic impact of large electricity supply interruptions remains limited (Linares and Rey, 2013). This is mainly because such interruptions are rare events and the data about them is thus scarce. An optimal response to these events

[2] For example, on 17 December 1978, almost the entire French electricity system failed (except in regions which were supplied by Germany) for around 2 hours and 15 minutes in the morning and resulted in a cost of more than US$1 billion in terms of lost production (Sanghvi, 1982).
[3] An example is the major blackout in the US in August 2003. This event triggered several cascading effects, for example: traffic lights went off, computer systems were affected, trains and subways were disrupted, the banking and financial sectors were severely affected, health care was only able to work on emergency power (if available) or had to close, sporting events were cancelled, and schools closed (Min et al., 2007).

entails having better knowledge about their (economic) impact at sectoral and economy level. The insights into the effects would help to protect the critical infrastructures better in the event of major service disruptions and to minimize the economic and welfare consequences of cascading effects resulting from power failure.

Moreover, risk-informed decisions will help the development of investment strategies and the adoption of measures to reduce the overall risk (Conard et al., 2006). Also, concerns such as how to design contingency plans to minimize the economic impact of power outages can be assessed when the most vulnerable sectors to interruptions are identified. Additionally, a related policy concern is the level of investments required to prevent major incidences in the power sector. An estimate of societal costs of major service interruptions is useful for planning and decision making as it can be used to calculate the amount that the society need to invest in order to avoid catastrophic events (given the probability of these events) (Pindyck and Wang, 2013).

This paper investigates the interdependency effects and economic impact of power supply disturbance through a Dynamic Inoperability Input–output Model (DIIM) applied to 101 sectors of the Scottish economy in 2009. Additionally, we use the DIIM model to estimate the societal cost of energy not supplied (SCENS),[4] taking into account the interdependencies among infrastructures.

The following section describes the sectoral interdependencies and discusses some of the previous approaches used to estimating the cost of power outages. Section 3 puts forward the methodology adopted to assess the impact of electricity supply disruptions on interdependent sectors of the economy and to compute the value of energy not served. Section 4 presents the results of applying this method to the case of the Scottish economy and discusses some policy implications. Finally, Section 5 gives the concluding remarks.

[4] We use the term 'societal' because SCENS includes the cost to both the power sector and to the rest of the economy resulting from interruption.

2. Sectoral interdependency and power interruptions

Better knowledge of the economic impact of electricity supply disruptions is important for regulators and policy makers, given the extensive interdependencies between the power sector and other infrastructure industries. These interdependencies generally fall into four categories: geographical, logical (also called procedural), cyber, and physical (Rinaldi et al., 2001; Dudenhoeffer et al., 2006). Geographical interdependency is related to locational proximity. Procedural interdependency is due to protocols such as a halt in operations due to a security threat. Cyber and physical interdependency reflect engineering reliance to inputs (in the form of data or physical materials) from other infrastructures.

The physical and cyber interdependencies between the electricity sector and the rest of economy are highly susceptible to shock transmission. This stems from the central position of electricity in modern economies. For instance, all sectors of the economy use electricity directly as an input in the production process, or indirectly to support a production process. In turn, the power sector itself relies on inputs from other sectors. Therefore, the system of interdependent infrastructures is capable of transmitting power failures shocks that can cause unforeseen repercussions throughout the economy. Furthermore, with the increased use of information and communication technologies in the power industry, there is a strong element of informational reliance between the electricity system and other infrastructures, thus further increasing the intricacy of the interdependencies.

Other forms of interdependencies can also be related to the power sector. For example, there is often some geographic proximity between the power grid infrastructure and telecommunication networks (such as telephone lines) or transport infrastructures (such as railways). Such proximity can influence the functionality of these infrastructures when an event causes damage to one of them. This suggests that reliable operation of the interdependent infrastructures is fundamental to preventing the costly consequences of cascading effects in the event of failure. Also, it underlines the role of regulation and policy in incentivizing resiliency enhancement in the critical infrastructures.

The cost of energy not supplied can be used by the sector regulator when incentivizing power quality and resiliency improvements. More accurate estimations of the societal cost of interruption allow policy makers to make better investment decisions in resiliency enhancement and contingencies. However, the complexity of modern economies makes this a challenging task. Moreover, there are significant differences in the estimated value of lost load among the current studies (see Table 1). This is partly related to the differences in the approaches taken and to the structures of economies investigated.

Previous studies mainly revolve around two main approaches to estimate the cost of energy not supplied (although there are more potential approaches). Some studies use surveys to elicit consumers' preferences based on their willingness to pay (WTP) for reliable services or willingness to accept (WTA) interruptions. The second approach is based on production functions which relate electricity consumption to the value of the output of firms, or the time spent on non-paid work in the case of households (Leahy and Tol, 2011). In this approach, the gross value added (GVA) of a sector is divided by the electricity used in the sector in order to estimate the output value of each unit of electricity supply. This figure is then used as an estimation of the loss of output for each unit of electricity not supplied. Table 1 summarizes selected previous studies on the cost of electricity interruptions using these two approaches.[5]

There are, however, several issues with the above two approaches. Firstly, the implementation of comprehensive surveys that accurately reflect the preferences of all consumer categories is time consuming and costly. Secondly, there are issues with surveys, such as the possibility of poor measurement, omission of relevant cases, and non-response. The production function approach has also drawbacks. For example, the ratio of GVA to electricity consumption in a given sector, only reflects the average productivity of electricity in that sector. Thus the relationship of this with the true value of the interruption cost is slight as it only shows the value added from electricity under the normal production process; this does not necessarily hold during an interruption due to disequilibrium, interdependency, and associated effects.

[5] A detailed overview of the studies of interruption costs and their approaches is given in Toba (2007).

Table 1: Summary of selected studies of cost of power interruptions

Study	Country	Year	Method	Estimated costs	Adjusted costs (2009 prices)
Leahy and Tol (2011)	Ireland	2007	Production function	Total €12.9/KWh	€13.63 /KWh
Balducci et al. (2002)	USA	1996	Surveys	Total $8.76/KW (1 h)	€8.55/KW (1 h)
Nooij et al. (2007)	Netherlands	2001	Production function	Total €8.56/KWh	€10.27/KWh
Diboma and Tatietse (2013)	Cameroon	2009	Survey	€3.62 to 5.42/KWh for a 1-h interruption and €1.96 to 2.46/kWh for a 4-h outage.	€3.62 to 5.42/KWh for a 1-h interruption and €1.96 to 2.46/KWh for a 4-h outage.
Reichl et al. (2013)	Austria	2011	Production function and survey	€17.1/ KWh	€16.80/ KWh

Furthermore, many earlier studies estimate the cost of power outage as a constant function in terms of $/KW or $/KWh without taking into account the time dependency of the outage cost (Lo et al., 1994). Additionally, perhaps the most serious shortcoming of the aforementioned approaches when estimating the societal cost of interruptions is that they do not allow for the interdependency effects among the infrastructure sectors. Interdependency can become more significant with increased duration of the interruption, because the higher order and induced effects can cause additional costs. Therefore, given the issues with the traditional approaches used in the previous literature, we use a dynamic inoperability input–output model. The method adopted in this study not only accounts for the sectoral interdependencies but also captures the time dependencies of interruption costs.

Another important point, which is often overlooked, is the class of outages for which a specific type of method is suitable. Weather-related incidences – such as wind, lightning, snow, rain, ice, and dust events – are among the most important causes of power outages. Other factors can also affect network operational conditions – such as when animals, trees, vehicles, or flying objects come into contact with power lines, fuses, and other equipment – resulting in power faults and consequent blackouts. In addition, equipment failure and surplus or insufficient demand can cause outages; the need for planned outages must also be taken into account. In recent years, with an increase in the share of renewable resources, the risk of power outage has increased due to both under and oversupply of energy from stochastic sources, such as wind and solar power. This is because supply variability can lead to grid instability as it affects frequency.

However, none of the existing methods covers all types of power outages. The approach adopted in this study (DIIM model) is mainly suitable for the class of outages which is related to the networks, it thus covers a wide range of outage types. This is reasonable given that more than 90 per cent of power outage incidences are related to the grid (Hammond and Waldron, 2008). Furthermore, electricity distribution networks are often composed of hundreds of thousands of kilometres of overhead lines and underground cables which can be easily exposed to extreme weather conditions.

3. Methodology

As mentioned, we use a dynamic inoperability input–output model (DIIM) to assess the direct, indirect, and induced impacts of power supply interruptions on different sectors of the economy. Input–output models are effective tools for investigating the spread of failure and recovery in a system of interdependent infrastructures (Ward, 2010).

DIIM has several advantages and features which makes it the method of choice for our type of analysis. First, unlike traditional approaches, DIIM takes a holistic view of the economy which also takes the interdependencies between the different sectors of the economy into account. Second, DIIM allows for intertemporal analysis; this has proved to be useful given that the cost of outages tend to change with duration of interruptions (most traditional methods do not have the capacity to capture the dynamic nature of power cuts). Finally, the DIIM enables us to distinguish between inoperability and the economic loss effect of power outages.

The inoperability input–output model (IIM), as a derivative of the Leontief model, was first introduced by Haimes and Jiang (2001) to model interdependent infrastructure sectors. It was later developed further by Santos and Haimes (2004) to quantify the impact of terrorism on critical infrastructures. Other studies using the IIM approach and its variations to investigate the behaviour of interdependent infrastructures include Haimes et al. (2005a; 2005b), Setola et al. (2009), Crowther and Haimes (2010), and Oliva et al. (2011).

The simple form of a Leontief input–output model (see Leontief, 1936; Santos, 2006) can be written as in (1).

$$X = AX + C \qquad (1)$$

where C denotes the demand vector, which is the amount of product that consumers consume. X represents the total production which is required to satisfy the demand vector C. The technology coefficient matrix A describes the relations among the sectors of the economy. Each column vector of the matrix represents a specific industry, while each corresponding row vector represents the amounts that each industry contributes as an input into the industry represented in each column.

In a similar manner, the general form of the IIM model can be presented as in (2) (Santos and Haimes, 2004; Santos, 2006)[6]

$$q = A^{*}q + C^{*} \qquad (2)$$

where q is an inoperability vector which is defined as the ratio of unrealized production to normal production[7]. A^{*} is the interdependency matrix which presents the degree of correlation among different industry sectors. C^{*} is the demand disturbance vector which is the ratio of demand reduction over the normal production level.

[6] See Haimes et al. (2005a) for a description and derivation of the IIM model from the Leontief equation.

[7] An important point to consider is that inoperability in this study is defined for a sector and not for a single production unit (a sector is a set of many production units). A partial disruption to an input (for example, electricity) can make a sector partially inoperable because while some production units become fully inoperable many others are not affected by power disruption. However, for a single production unit lack of an input such as electricity can disrupt the whole production process irrespective of how much of other inputs are available.

Equation (3) thus represents the demand side perturbation where $\hat{c}$ and $\tilde{c}$ are normal demand and reduced demand respectively, and $\hat{x}$ is planned production. The assumption of non-zero production values for each industry guarantees the existence of $diag(\hat{x})$ inverse, which is also a diagonal matrix.

$$C^* = [diag(\hat{x})]^{-1}[\hat{c} - \tilde{c}] \qquad (3)$$

$$\begin{bmatrix} c_1^* \\ \vdots \\ \vdots \\ c_i^* \\ \vdots \\ \vdots \\ c_n^* \end{bmatrix} = \begin{bmatrix} \frac{1}{\hat{x}_1} & 0 & \dots & \dots & 0 \\ 0 & \ddots & \ddots & 0 & \vdots \\ \vdots & \ddots & \frac{1}{\hat{x}_i} & \ddots & \vdots \\ \vdots & 0 & \ddots & \ddots & 0 \\ 0 & \dots & \dots & 0 & \frac{1}{\hat{x}_n} \end{bmatrix} \begin{bmatrix} \hat{c}_1 - \tilde{c}_1 \\ \vdots \\ \hat{c}_i - \tilde{c}_i \\ \vdots \\ \hat{c}_n - \tilde{c}_n \end{bmatrix}$$

It is evident that we always have $0 \leq C_i^* \leq \frac{\hat{c}_i}{\hat{x}_i}$ where $i \in \{1, .., n\}$. The lower limit corresponds to the case that reduced demand is the same as normal demand, so there is no deviation from the steady state. However, when the reduced demand is zero, the deviation is maximized, equalling the upper limit of the aforementioned inequality.

The interdependency matrix, A^*, is related to the Leontief technical coefficient matrix A, and vector of normal production of industries as in (4).

$$A^* = [diag(\hat{x})]^{-1}[A]\,[diag(\hat{x})] \qquad (4)$$

If we substitute (4) and (3) into (2) we obtain (5):

$$q = [diag(\hat{x})]^{-1}[A]\,[diag(\hat{x})]q + [diag(\hat{x})]^{-1}[\hat{c} - \tilde{c}] \qquad (5)$$

which presents the inoperability vector q in terms of planned production, the Leontief technical coefficient matrix, normal demand, and disturbed demand. It can be shown that the inoperability vector q is between zero and one (see Santos and Haimes, 2004). When q is equal to zero, there is no disruption and production is 'business-as-usual'. In the extreme case where q is equal to one, the production process is completely disrupted.

The IIM model can be extended to represent a dynamic inoperability input–output model (DIIM), by introducing the dynamic aspect of interdependent economic systems and resiliency of the sectors, as in (6) and (7) (see Haimes et al., 2005a; Orsi and Santos, 2010).

$$q(t+1) = q(t) + K[A^* q(t) + c^*(t) - q(t)] \tag{6}$$

where K is a resiliency matrix and its elements show how the system responds to disequilibrium and t is time period. The relation in (6) can be approximated with a differential equation as in (7).

$$\dot{q}(t) = K[A^* q(t) + c^*(t) - q(t)] \tag{7}$$

As seen from equations (6) and (7), the inoperability in each period is equal to the inoperability in the previous period plus a partial adjustment of inoperability due to resiliency. The value of the resiliency matrix can be either negative or zero. Under the condition that resiliency is zero, the inoperability does not change over time and these equations will be the equivalent of the static IIM formula in (2). However, when the resiliency matrix is negative, it can be seen from (6) and (7) that inoperability will eventually decrease over time. The coefficients of the resiliency matrix depend on the characteristics of the industry and on the risk mitigation policies implemented. In other words, the resiliency of the sector can be controlled through risk mitigation measures such as redundancy, which consequently reduces the recovery time and financial losses following a disturbance.

The general solution to the differential equation in (7) will be as in (8) (Haimes et al., 2005a).

$$q(t) = e^{-K(I-A^*)t} q(0) + \int_0^t K e^{-K(I-A^*)(t-\xi)}\, C^*(\,\xi) d\xi \tag{8}$$

The assumption of stationarity of final demand, c^*, allows us to simplify (8) further as follows:

$$q(t) = (I - A^*)^{-1} c^* + e^{-K(I-A^*)t}[q(0) - (I - A^*)^{-1} c^*] \tag{9}$$

$$q(t) = q_\infty + e^{-K(I-A^*)t}[q(0) - q_\infty] \tag{10}$$

where q_∞ is the steady state (equilibrium) level of inoperability determined by final demand c^*, and $q(0)$ represents the initial inoperability imposed by the shock. As seen from (9) and (10), the term including $e^{-K(I-A^*)t}$ fades off over time and, in an infinite time horizon, these equations will converge to a static IIM.

A key feature of DIIM is the resiliency matrix coefficients, which show the response of individual industries to the imbalance between supply and demand. Under the conditions that $k_i > 0,\ a_{ij}^* = 0\ \ \forall\, i \neq j,$ and final demand remains constant, the following equation, based on (8), can be written:

$$q_i(t) = q_i(0)e^{-k_i(1-a_{ii}^*)t} \tag{11}$$

which leads us to obtain elements of the resiliency matrix as in (12).

$$k_i = \frac{\ln[q_i(0)/q_i(T)]}{T_i(1-a_{ii}^*)} \tag{12}$$

where $q_i(0)$ is the magnitude of initial inoperability of sector i imposed by the shock and T_i is the time taken by the sector to arrive at the inoperability level of $q_i(T_i)$. Naturally, the final level of inoperability must be lower than the initial inoperability level to ensure a positive k_i.[8] Finally, a_{ii}^* is the element of A^* that can be obtained using its relationship with the Leontief coefficient matrix A. The underlying assumption is that the resiliency of the sector solely depends on itself and not on the other sectors. Thus, the resiliency matrix is diagonal.

Under the input–output framework discussed above, the impact of a shock to any sector (e.g., the power sector) can be measured both in terms of inoperability (q) and economic loss (Q). The cumulative economic loss, over period of recovery, for an individual sector and for the whole economy (n sectors) can be obtained from (13) and (14) respectively.

$$Q_i(t) = \hat{x}_i \int_{t=0}^{t=T} q_i(t)dt \tag{13}$$

$$Q(T) = \sum_{i=1}^{n} \left(\hat{x}_i \int_{t=0}^{t=T} q_i(t)dt \right) \tag{14}$$

The concept of inoperability in our model corresponds to the reliability concept in the power sector. In the electricity industry, system reliability is usually defined as

[8] Because the resiliency matrix already has a negative sign, as seen from Equation (8).

$1 - \frac{unsupplied\ energy}{energy\ that\ would\ have\ been\ supplied\ without\ an\ interruption}$. Using a similar analogy we can compute the cost of supply disruption using the inoperability metric and societal cost of power sector inoperability as previously presented in (14). Thus, if E represents the total electrical energy that is normally delivered during each period, we can calculate the cost of a major supply disruption using relation (15):

$$SCENS = \frac{Q(T)}{E\int_{t=0}^{t=T} q_i(t)dt} \qquad (15)$$

where $SCENS$ is the socio-economic cost of energy not supplied and can be presented in terms of £/MWh or £/KWh. The term $E\int_{t=0}^{t=T} q_i(t)dt$ shows the total electrical energy interrupted during the outage, as a result of an inoperability shock $q_i(t)$ to power sector.

3.1 Household Sector

Sectoral input–output data do not render information about the value of leisure for the household sector while electricity is important for many leisure activities. Therefore, we extend our analysis to include also the effect of outages on this crucial sector. Obtaining accurate estimations of the economic cost of power outages for the household sector is a challenging task.

Valuation methods based on 'stated preference' are costly and can sometimes be misleading because it is hard to quantify the value of leisure by asking consumers about their willingness-to-pay for reliable service or willingness-to-accept an outage. Moreover, households' valuation of leisure time can change over relatively short time periods. Approaches based upon 'revealed preference', where the actual choices of households are observed, can be a proxy for consumer willingness to pay for continuity of supply (e.g., the amount invested by a household in backup generation to compensate for poor supply reliability). However, despite the appealing characteristics of this method, the problem of data availability and collection is often a major impediment.

An alternative method is to approximate the monetary value of utility derived from electricity-dependent leisure activities. Becker (1965) was among the first who attempted to estimate the value of lost leisure time. This approach is founded on the basic microeconomic theory that labour supply is the result of utility maximization of the households given the trade-off between leisure and income (or consumption if assuming all income is spent). Households supply their labour to other sectors of the economy and the time which is not spent on working or sleeping is referred to as leisure. Several studies have adopted this approach to quantify the value of lost leisure (see de Nooij et al., 2007; Wolf and Wenzel, 2014). Following this method, we estimate the value of leisure for the households and integrate this in our DIIM model as explained in the previous section.

The value of leisure is estimated indirectly through the opportunity cost of leisure. For an employed person, the marginal benefit of (last unit of) leisure must equate to its opportunity cost in terms of foregone income from labour (Burkett, 2006). In the case of unemployed persons, we need to consider the possibility of involuntary unemployment or unemployment due to low compensation. This implies that opportunity cost of leisure for an unemployed person can be lower than that of an employed. In order to account for this, we assume that the value of leisure for an unemployed person is a percentage of that of an employed person. Furthermore, since all leisure activities are not electricity-dependent, we adjust leisure times to reflect better the impact of power cuts.

Therefore, we can calculate the value of leisure to the household (CL_h) as follows:

$$CL_h = [\gamma(T - Wh)W]P_e + [\gamma T(\theta W)]\,(P - P_e) \qquad (16)$$

where γ is the percentage of electricity-dependent leisure activities, T is the total time available to spend for work or leisure, Wh is total working hours, W is average wage per hour, θ is a factor to adjust the opportunity cost of leisure for an unemployed person, P_e is the population of employed people, and P is the total population.

In the absence of information on either the stated or revealed preference of households, this method approximates the utility gained from consuming electricity. However, as noted in Wolf and Wenzel (2014), the flexibility assumed in allocation of time between work and leisure can be unrealistic given that working hours are specified by contracts, and some people may not work full time. Furthermore, people may adapt if they experience frequent power cuts. These factors are the shortcoming of this approach and cannot be fully accounted for using our adopted approach.

4. Application to the Scottish economy

4.1 Power interruption in Scotland

Electricity in Scotland is delivered by two electricity distribution networks operators (DNO). Scottish Hydro Electric Power Distribution (SSEH) operates in North Scotland and serves around 740,768 customers (Ofgem, 2012). SP Distribution (SPD), part of the Scottish Power Group, supplies electricity to over 1,990,000 customers in Southern and Central Scotland (Ofgem, 2012).

From a regulatory perspective, reliability of networks is crucial for a secure electricity supply. DNOs are expected to minimize outages in terms of frequency and restoration time. In order to incentivize the DNOs, the UK regulator (Ofgem) uses a penalty and reward scheme based on predefined performance targets. The main metrics are *CI*[9] and *CML* which reflect frequency and duration of power outage respectively. *CI* is defined as the number of interrupted consumers (per 100 customers) whom their supply cut lasted more than three minutes during a year. *CML* is the average customer minutes lost per customer during each year for outage duration of in excess of three minutes.

Figure 1 compares the *CML* (for unplanned outages) for the two Scottish DNOs with that of GB average over the period of 2003-10 inclusive. Figure 2 shows the *CI* for the same companies and the aforementioned period compared with GB average. Both figures indicate that over the past few years, Scotland has experienced power outages which are often higher in frequency and duration that of GB average. This is mainly because of weather related incidences which adversely affects the operation of the networks. Figure 3 shows frequency and duration of interruption for 2010-11. As can be seen from the figure, the majority of interruptions have been restored within 24 hours. This also implies sector resiliency as inoperability decreases over time.

[9] In order to distinguish *CI* as the metric for consumers' interruption and CI an acronym of critical infrastructure we present the former in italic format.

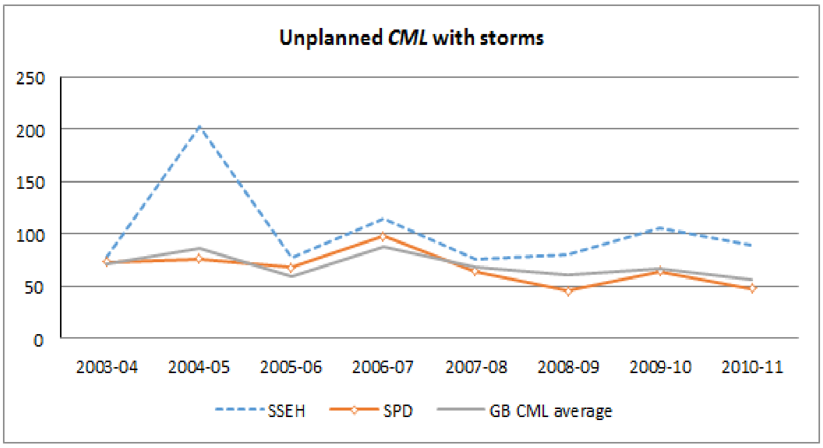

Figure 1: CML for unplanned outages
Source of data: Ofgem (2012)

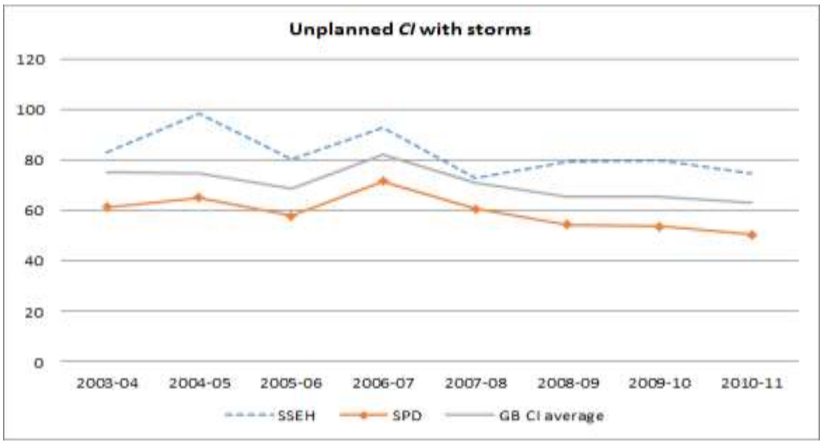

Figure 2: CI for unplanned outages
Source of data: Ofgem (2012)

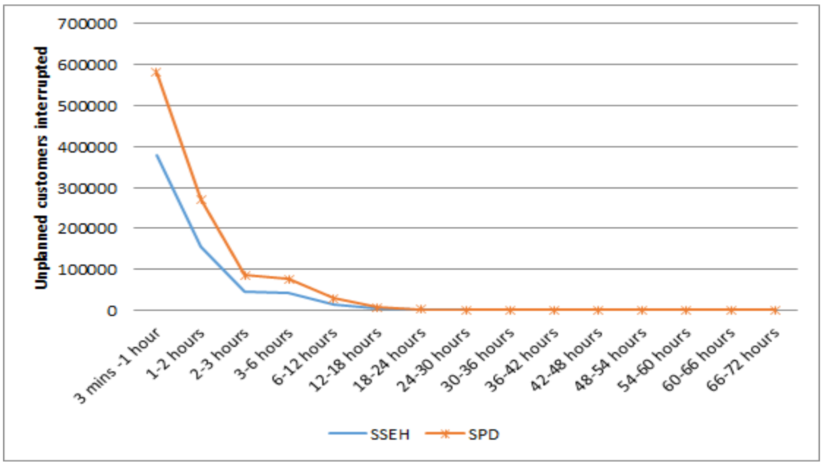

Figure 3: Frequency and duration of interruptions (unplanned outages) for 2010-11
Source of data: Ofgem (2012)

4.2 Scottish economy and data

We explore the economic impact and interdependency effects of power supply disturbance through a case study of Scotland. Following the industrial revolution, Scotland became a leader in manufacturing industries. This has left a legacy in the diversity of its goods and services. However, over time as in the rest of the UK, there has been a decline in manufacturing and primary based extractive industries, while the service sector has been on the rise. Scotland has oil and gas resources in the North Sea and a large potential for renewable energy sources such as wind and wave, and is a net exporter of electricity.

The economic activities of Scotland, as for any other modern economy, involve four types of primary activities: (a) production of goods and services by industries; (b) consumption of goods and services by industries and domestic final users (comprising mainly households and government, both local and central); (c) the accumulation of fixed capital and stock changes in the economy; and (d) trade which involves imports and exports to the rest of the UK and the rest of the world (Scottish Government, 2011b). The measurements of these four activities are represented in an input–output framework. The input–output data provides a comprehensive picture of the flow of goods and services in the economy in a given year. The data also describes the interaction between the producers and consumers, together with the details of interdependencies among the industries.

The data used in this study includes 101 industries in Scotland in 2009. The dataset contains the output of each industry as well as its reliance on other sectors, based on a Leontief coefficient matrix. The Leontief coefficient matrices are derived from the industry-by-industry matrix which shows how much of each industry's output is needed, in terms of direct and indirect inputs, to produce one unit of a given industry's output. Table A1 (Appendix) presents these industries which can be grouped under the following broad categories:

- Agriculture, forestry, and fishing,
- Mining,
- Manufacturing,
- Energy and water,

- Construction,
- Distribution and catering,
- Transport and communications,
- Finance and business,
- Public domain etc.,
- Education, health, and social work,
- Other services,
- Households.

The population of Scotland is slightly over 5 million; this number has remained stable in the past half century although recent immigration from the EU has supported a modest growth. Due to the general shift over the past 30 years from manufacturing to services, the service sector now accounts for around 75 per cent of the Scottish economy's output and 82 per cent of the employment, whereas manufacturing is 13 per cent of the total output with 7.5 per cent of total employment (Scottish Government, 2011a). According to the 2011 Annual Population Survey, around 73.6 per cent of the Scottish population were in full time employment (73.8 per cent in 2010 and 76.2 per cent in 2008) (Scottish Government, 2012). Furthermore, 8.3 per cent of the employed people were underemployed – in other words, searching for extra hours in their current job. Table 2 presents a summary statistics for the Scottish economy in 2009.

Table 2: Summary statistics – Scottish economy (2009)

Population	5,194,000
GDP (£m)	106,781.5
Electricity sales (public supply) (GWh)	29,955
Total domestic electricity consumption (GWh)	11,434.8270
Commercial and industrial total sales (GWh)	15,631.8888
Average domestic electricity consumption per capita (kWh)	2201.5454
Population in employment	2,529,000
Average hourly earnings (full-time employee)	£11.98/hour

Sources: Scottish Government Input-Output Tables 2009; Scottish Government Energy Statistics Database (2014); Scottish Government Annual Population Survey (2009); Office for National Statistics (2014)

Leisure activities in Scotland are similar to those in the rest of the UK and are not entirely electricity-dependent. In order to evaluate the effect of power cuts on households we need to specify the percentage of leisure time which relies on electricity supply (parameter γ in equation 16). It is clear that $0 < \gamma < 1$. Some studies have assumed that only half the leisure activities require electricity (see Growitsch et al., 2013). Other studies assume this figure to be higher (e.g., 65 per cent in Wolf and Wenzel, 2014). According to the office for national statistics (ONS) (2011), in 2009/10, adult people aged 16 and above in the UK spent, on average, 3.5 hours a day watching TV, 2.5 hours using a computer, and one hour listening to the radio. If we consider other indoor and outdoor activities – such as holidays and day trips, sporting, social and political participation, shopping, eating out, cinema, and religious activities – we can observe that a large portion of mainstream leisure activities are electricity-dependent. There are of course activities that do not require electricity directly – such as reading in daylight or walking – however, these are often a small portion of the leisure time for most people. Therefore, following Wolf and Wenzel (2014) we assume that γ is 65 per cent. Furthermore, we assume that the opportunity cost of leisure for unemployed people is half that for the employed (de Nooij et al., 2007).

4.3 Scenario generation and framework

The scenario generation process involves specifying the initial inoperability vector (q_0), recovery time (T), and final level of inoperability (q_T). For example, we specify the initial inoperability as a shock to the electricity industry which disrupts q_0 percentage of electricity supply (e.g., 5 per cent); this figure diminishes exponentially, with a final level of inoperability of q_T (e.g., 0.001) achieved after T period (e.g., 12 hours). The perturbation vector for all sectors can be obtained using the share of their output reliance on electricity as follows:

$$q_i = q_0 \frac{u_i}{\max(u_i)} \tag{17}$$

where q_i is the perturbation to sector i as a result of q_0 shock to the electricity industry and u_i is the share of electricity in the output of industry i divided by the share of electricity in the output of the maximum consuming sector. As electricity has the highest share in the output of the electricity industry itself, the relation in (17) results in an inoperability of q_0 in the electricity industry and a proportional inoperability for other industries based on their electricity usage. In the absence of data on the recovery process of each individual industry, we assume a similar recovery period, T, for all sectors as for the perturbed sector. This is because, as noted in Santos (2012), if a given sector is dependent on the perturbed sector it will follow the same recovery path as the initially perturbed sector. However, if a given sector does not rely upon the perturbed sector it will not be affected by the initial shock, irrespective of the recovery period chosen. The recovery period T can be as short as few minutes or as long as days or weeks.

A systemic analysis will be carried out by considering various sources of uncertainty – such as the degree of perturbation of the initially affected sector and temporal issues around sector recoveries. We compare inoperability with economic loss and identify the sectors most vulnerable to electricity supply disruptions in Scotland. Also, we will analyse the robustness of the ranking of vulnerable sectors to different durations and extents of power supply interruptions. Finally, we compute the cost of 'energy not supplied' in Scotland for different inoperability levels and periods of interruption.

4.4 Results and discussion

A power outage shock propagates rapidly and affects the whole economy through direct and indirect effects. These effects are more apparent in industries with higher levels of interdependency with the power sector. Figure 4 depicts the impact of power sector perturbation in terms of inoperability variation over the period of recovery. The figure presents a scenario where a shock is applied to the power sector with an initial inoperability level of 5 per cent which declines exponentially to 0.001 after 12 hours (720 minutes). In order to trace the effect of this inoperability shock we have selected six sectors, of which five are critical infrastructures, for illustration purpose. These sectors are: gas, water, telecommunication, financial service, coal industry and the household sectors in Scotland.

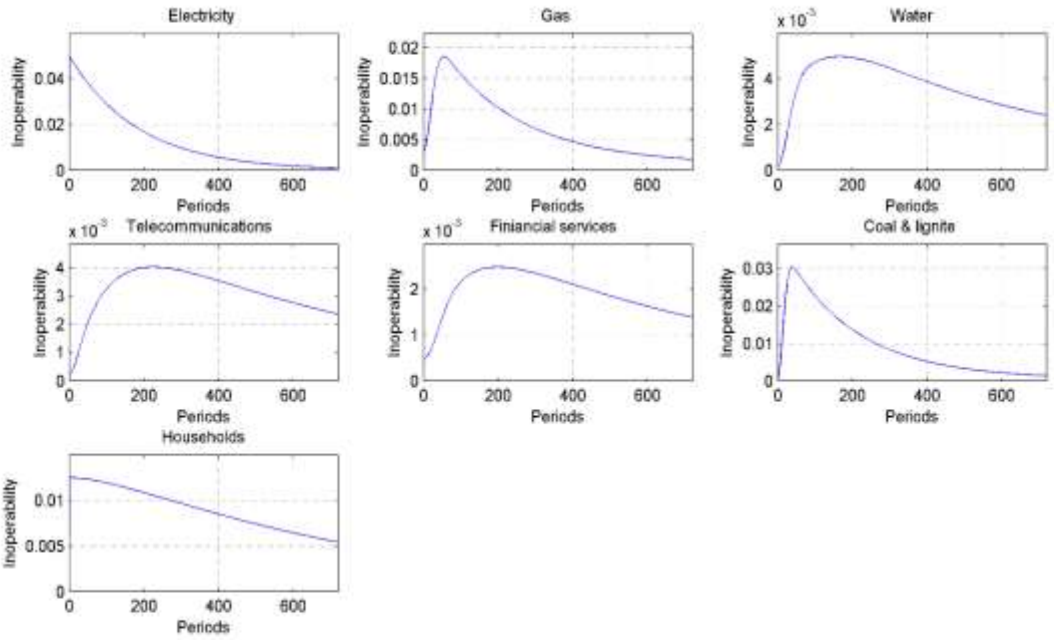

Figure 4: Inoperability change over the recovery period in selected sectors

Source: Authors

As shown in Figure 4, the affected sectors follow a similar recovery path but with different levels of inoperabilities over time. In all cases, inoperability initially increases until it reaches a maximum and then begins to decline. In the absence of resilience, inoperability will not decline, but will instead reach a new steady state. However, in practice, inoperability decreases because the perturbed sector (the power sector in this case) and other infrastructures are assumed to follow a recovery process (in other words, they are resilient). The inoperability following the electricity supply disruption can be the result of direct, indirect, and induced effects.

A sector becomes inoperable in a scenario such as that outlined above if electricity is an important input in its production process. In the case of household lack of electricity disrupts the capacity for electricity-dependent leisure activities. Furthermore, as it is seen from the Figure 4, the resulting induced inoperability is relatively high (around 1.5 percent at the beginning) due to sensitivity of the household activities to power cut.

Similarly, a sector can become inoperable if it supplies the inputs (such as gas or coal) of the electricity industry. This is because interruption in electricity services damages the business of the sectors that supply its inputs. Therefore, inoperability is not limited to the unidirectional effects of interrupted power as an input to other industries; it also embraces the sectors on which the electricity industry relies.

For example, as seen from Figure 4, the inoperability of the coal industry progresses rapidly following an electricity disruption until it reaches slightly over 3 per cent (after approximately 40 minutes) and then the recovery starts. This means that the coal industry is highly affected, directly and indirectly, by the initial inoperability shock to the power sector. The main source of the inoperability impact on the coal sector, however, is that the Scottish electricity industry is highly dependent on coal. Thus, when an event interrupts the electricity industry it will also disrupt the coal sector. A similar situation holds for the gas distribution network, though with a lower peak inoperability.

The marked reliance of the electricity sector on coal and gas can also be seen from Figure 5, which shows the share of electricity generation by fuel type in Scotland in 2009. At the same time, both of these sectors consume electricity in their own production process- an example of the interdependencies among the industries within the energy sector.

Although all the sectors follow a similar recovery path, the graphs in Figure 4 show a weaker inoperability for the water, financial services, and telecommunication industries. Also, their recovery takes slightly longer than that of the gas and coal industries. The lower inoperability in these sectors can be due to the lower level of interdependency between these industries and the power sector, as opposed to the case of coal and gas infrastructures. In other words, the greater the interdependency between the affected infrastructures and the initially perturbed sector, the higher will be their inoperability over the period of recovery.

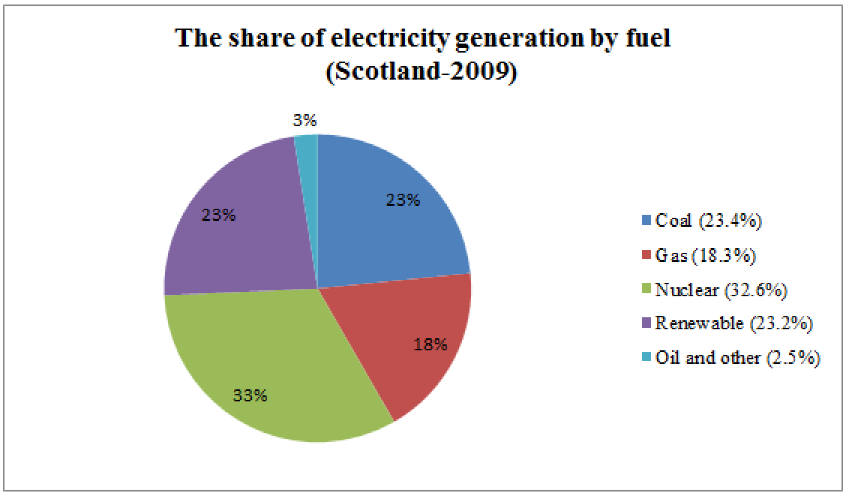

Figure 5: The share of electricity generation by fuel in Scotland

Source of data: Scottish Government Energy Statistics Database (2014)

Figure 6 illustrates the top 10 sectors with the highest levels of inoperability during the recovery time. Figure 7 depicts the sectors incurring maximum economic loss over the aforementioned period. As can be seen from both figures, with the exception of the power sector (the initially perturbed industry) which has the highest rank in terms of both inoperability and economic loss, the remaining sectors do not hold the same ranking orders. For instance, the coal and lignite sector is ranked second for inoperability and the household sector is ranked forth (Figure 6), while they do not appear among the 10 most highly affected sectors in terms of economic loss (Figure 7). Conversely, the health sector appears to be highly affected financially (Figure 7) whereas it is not among the top 10 in terms of inoperability (Figure 6). A similar situation holds for other sectors.

These results suggest that inoperability does not directly translate to a corresponding level of economic loss. In effect, the sensitivity of revenue and operational status to a particular input (e.g., electricity) varies across and within industries. This is due to the fact that operational responsiveness depends on occurrence of indirect effects, the importance of power as input in production, and flexibility of the production processes. On the other hand, economic responsiveness depends on the value of produced goods or services which have been disrupted as a result of inoperability shock.

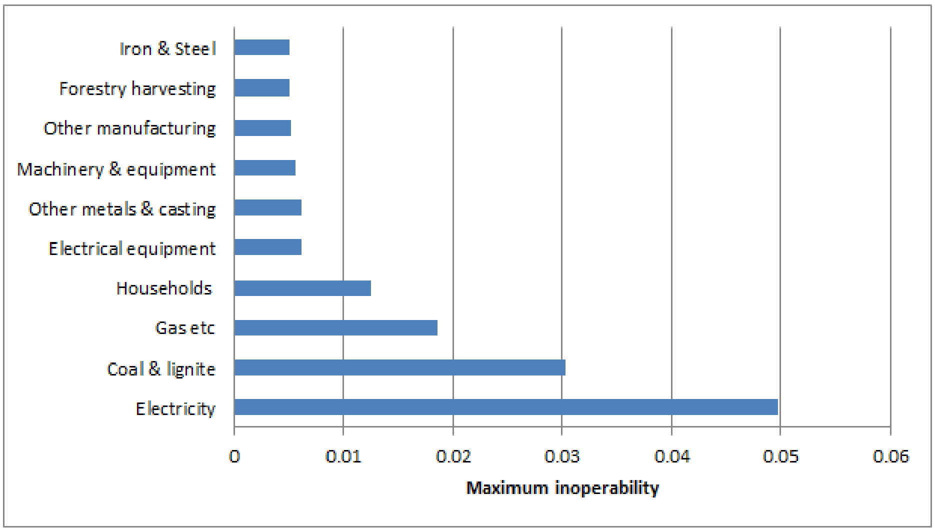

Figure 6: Top 10 sectors with highest inoperability over the period of recovery

Source: Authors

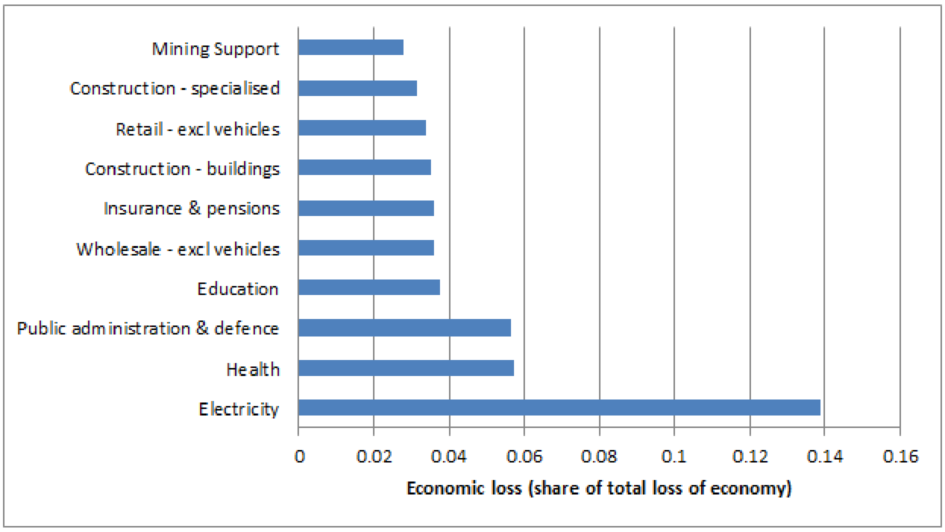

Figure 7: Top 10 sectors with highest economic loss over the period of recovery

Source: Authors

These findings lead us to make a distinction between the operational responsiveness of a sector and its economic sensitivity to an input shock from the initially perturbed industry. The implication of this for critical assets is that prioritizing for the preservation of a sector during an extreme event should be based on some weighted average index that contains information about its operational status and economic loss, as well as its importance for the welfare and well-being of the population. A notable example is the household sector which becomes highly inoperable following power cut but the economic loss of the sector is not significant. However, due to societal implications, reducing the probability of outage in household sector has always been an important component of regulation for reliable services.

The results in Figures 4, 6, and 7 are based on an arbitrary recovery period of 12 hours and an arbitrary shock with initial inoperability level of q_0=0.05 for the electricity sector; and proportional for other sectors depending on their electricity usage. A valid query is whether the ranking of sectors based on inoperability and economic loss is sensitive to the chosen level of initial shock or recovery period. In order to investigate this, we analyse two cases with several underlying scenarios. In the first case, we assume different inoperability levels of 20, 40, and 80 per cent for the power sector, with a common level of recovery period of 12 hours. In the second situation, we investigate a common inoperability level of 15 per cent but different recovery periods of 1, 3, and 6 hours. In all these cases, the power sector is assumed to become 99.999 per cent operable after the recovery period. The results of the above sensitivity analysis for inoperability and economic loss are shown in Tables 3 and 4 respectively.

As Table 3 shows, there is no change in the ranking of the top ten sectors in terms of inoperability when different levels of shocks are assumed for the power sector (Case 1). This is also largely the case when different recovery periods are considered (Case 2), where some sectors shift one place up or down at some duration of recovery. Indeed, for three- and six-hour outage durations (second and third columns of Case 2) the ranking of sectors matches that in Case 1 except that the eighth sector is now ‘mining support’ rather than ‘other manufacturing’. For one hour of outage duration, the ranking of sectors is somewhat different, although it contains broadly the same sectors identified previously, except for ‘repair and maintenance’. Therefore, the top ten sectors, in terms of inoperability, are almost invariant with changes in the extent and duration of interruptions.

Table 3: Sensitivity analysis of inoperability ($q_T = 0.001$)

	Case 1				Case 2		
Top ten sectors	q_0=0.20 T=12 h	q_0=0.40 T=12 h	q_0=0.80 T=12 h		q_0=0.15 T=1 h	q_0=0.15 T=3 h	q_0=0.15 T=6h
1	SE45	SE45	SE45		SE45	SE45	SE45
2	SE6	SE6	SE6		SE6	SE6	SE6
3	SE46	SE46	SE46		SE101	SE46	SE46
4	SE101	SE101	SE101		SE46	SE101	SE101
5	SE38	SE38	SE38		SE8	SE38	SE38
6	SE35	SE35	SE35		SE35	SE35	SE35
7	SE39	SE39	SE39		SE38	SE39	SE39
8	SE43	SE43	SE43		SE39	SE8	SE8
9	SE3	SE3	SE3		SE3	SE3	SE3
10	SE34	SE34	SE34		SE44	SE34	SE34

SE45=Electricity,
SE6=Coal & lignite,
SE46=Gas etc.,
SE35=Other metals & casting,
SE38=Electrical equipment
SE44=Repair & maintenance
SE39=Machinery & equipment,
SE3=Forestry harvesting,
SE43= Other manufacturing,
SE34= Iron & Steel,
SE101=Households
SE8= Mining Support

A similar result can also be seen in Table 4 for the top ten sectors in terms of economic loss. Again some sectors shift one place up or down at some inoperability levels or recovery periods. However, these are the same previously identified top ten sectors in terms of financial loss (see Figure 7). The result of the sensitivity analysis offers confidence that the ranking of the different sectors in terms of their inoperability and economic loss is almost independent of the initial shock and recovery period assumed for analysis.

Table 4: Sensitivity analysis of economic loss ($q_T = 0.001$)

	Case 1				Case 2		
Top ten sectors	q_0=0.20 T=12 h	q_0=0.40 T=12 h	q_0=0.80 T=12 h		q_0=0.15 T=1 h	q_0=0.15 T=3 h	q_0=0.15 T=6 h
1	SE45	SE45	SE45		SE45	SE45	SE45
2	SE91	SE91	SE91		SE91	SE91	SE91
3	SE89	SE89	SE89		SE89	SE89	SE89
4	SE90	SE90	SE55		SE55	SE90	SE90
5	SE55	SE55	SE90		SE8	SE54	SE54
6	SE71	SE71	SE71		SE54	SE55	SE71
7	SE50	SE50	SE50		SE90	SE50	SE50
8	SE54	SE54	SE54		SE50	SE71	SE55
9	SE52	SE52	SE52		SE71	SE52	SE52
10	SE8	SE8	SE8		SE52	SE8	SE8

SE45=Electricity,
SE89=Public administration & defence,
SE91=Health,
SE55=Retail – excl. vehicles,
SE54=Wholesale – excl. vehicles,
SE8= Mining Support
SE50=Construction – buildings,
SE90=Education,
SE52=Construction – specialized,
SE71=Insurance & pensions,

The inoperability and economic loss metrics provide a picture of the vulnerability of infrastructures following electricity supply disruptions, based on an *ex ante* analysis. This information is important in policy making, to enable risk management and investment to protect critical assets against extreme events. As the inoperability ranking order does not necessarily coincide with economic loss, an integrated form of these metrics is required to make a better reflection of the situation following a power cut. This analysis has been presented in Figure 8.

Figure 8 provides the matrix of inoperability and economic loss impact for the top 10, 20, and 30 sectors (horizontal axis – economic loss; vertical axis – inoperability). Any sector on the diagonal of this matrix is equally important from inoperability and economic loss perspectives. Those that are above the diagonal are affected more financially while those that lie below the diagonal are affected more operationally. As shown in Figure 8, in each zone there are a few sectors that are vulnerable both from the operational and economic metric perspectives (although the top 10 zone only contains the electricity sector, implying that inoperability and economic loss follow a different ranking order in this zone). Other sectors such as: gas, wholesale, the coke, petroleum and petrochemical products, mining support, and fabricated metals are located in the top 20 zone. Overall, the matrix identifies 14 sectors as vulnerable, when considering the integrated metrics of inoperability and economic loss based on an *ex ante* analysis.

The *ex ante* analysis of infrastructure vulnerability to power loss is important for policy making; however, it does not replace the need for an *ex post* evaluation of vulnerable sectors. This is because some sectors may not appear in the ranking order presented in Figure 8, although their functioning is critical during a major outage. For instance, backup generators to support telecommunication systems during a major blackout are not normally deployed, and there is little economic incentive to deploy these costly arrangements (O'Reiley and Chu, 2008). However, for the purposes of crisis management, the perceived good of society, and in order to provide access to emergency services during a blackout, it may be desirable to supply such cross-infrastructure backup. A similar situation holds for emergency services and water industry, among others.

The above analysis shows the importance of reliable power supply given the interdependency among sectors and the consequent effects on the cost to society of energy not supplied. The societal cost of energy not supplied (SCENS) is among the important motives for investment in resiliency and reliability. In many countries, the regulatory framework of electric utilities is designed in such a way that SCENS affects their revenues directly or indirectly. Therefore, the utility companies have an incentive to minimize this cost by reducing the duration and frequency of interruptions, as well as the number of affected customers.

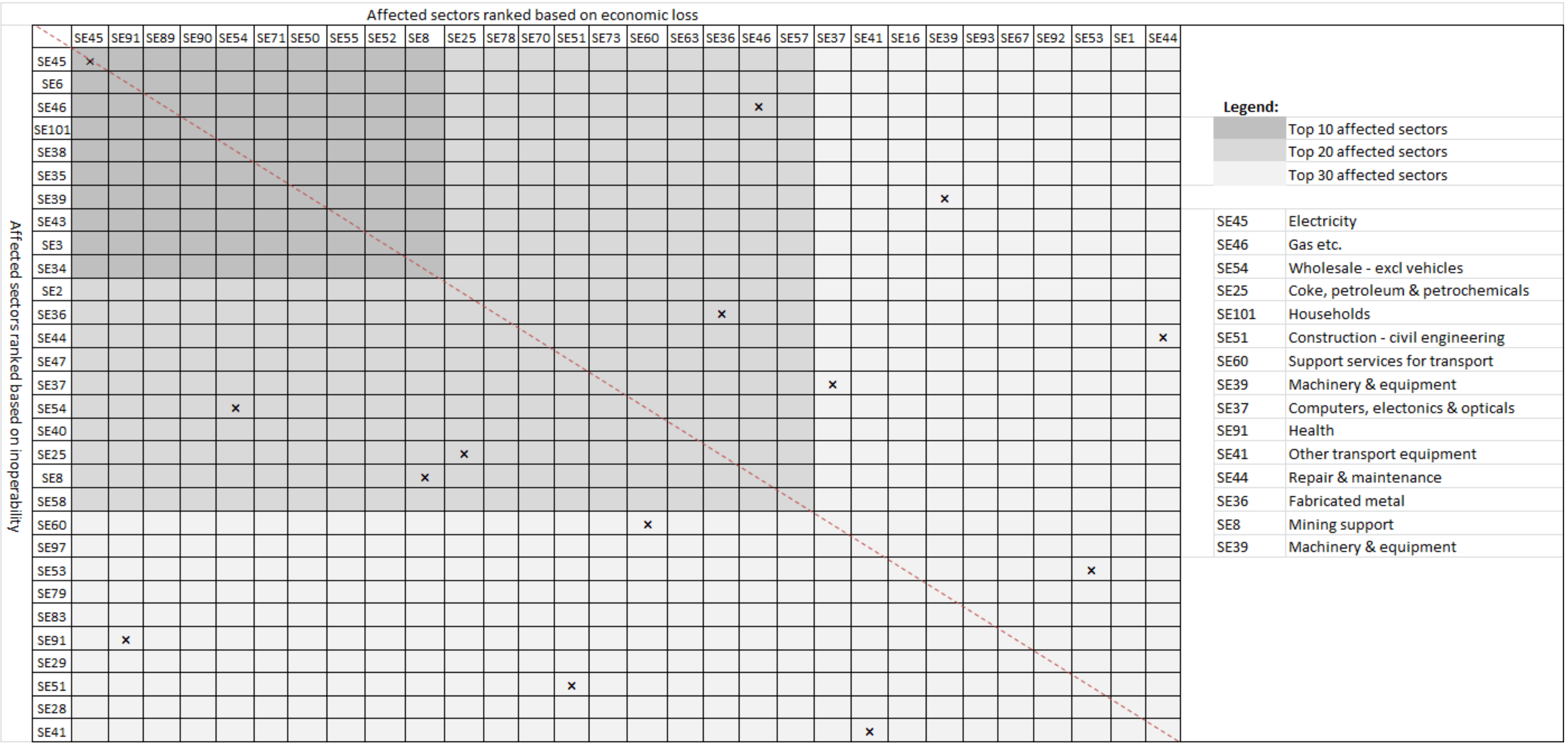

Figure 8: The matrix of inoperability and economic loss impacts

Source: Authors

Figure 9 presents the societal cost of energy not supplied (SCENS); estimation of this is based on a range of different inoperability levels for the power sector and on a duration of interruption of up to 360 minutes (6 hours). The inoperability levels assumed are 5, 20, 40, 80, and 100 per cent (blackout), and they decrease exponentially as explained and presented previously. The SCENS is estimated in terms of £/MWh of electrical energy interrupted, using total inoperability of the power sector over the period of recovery and the assumption of uniform electricity supply in each period if there was no interruption. Figure 9 shows that SCENS changes by only a trivial amount with the extent of interruption (different inoperability levels). For example, the graph shifts slightly upward when the level of inoperability increases from 5 percent towards 100 per cent. Thus, we can conclude that SCENS is almost independent of the extent of interruption. This also coincides with intuition as we would expect to see SCENS varying only with duration of outages.

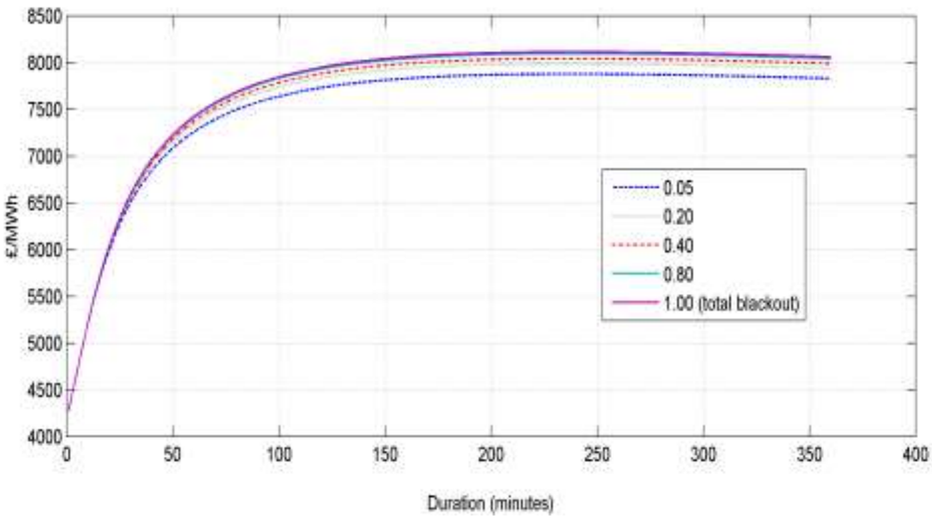

Figure 9: Societal cost of energy not supplied (SCENS) for Scotland – 2009 prices

Source: Authors

As seen from Figure 9, in all scenarios SCENS starts from around £4,300/MWh for a 1 minute interruption and increases with the increased duration of the power cut. The SCENS then rises rapidly to more than £7,000/MWh for a duration of around an hour, after which time its rate of increase slows. Also, the graphs show that regardless of the initial level of inoperability, all scenarios converge to around £8,000/MWh after two and a half hours. That is to say, for service interruptions lasting for three hours and over, SCENS ranges from £7,865/MWh at 0.05 inoperability level to £8,100/MWh for a total blackout.

Additionally, these results show that figures obtained using SCENS are significantly higher than those derived using traditional measures of societal cost of interruption (obtained by dividing GDP by total electricity sales in economy). Using the information in Table 2, we calculate this figure as £3,564.73/MWh. This is the average productivity of electricity for the Scottish economy and shows how much each megawatt-hour of electricity contributes towards GDP. With increased duration of interruption, this figure underestimates the societal cost of interruption to a greater extent. Furthermore, although the cost of energy not supplied depends on the structure of economies, and cross country comparisons may not be very accurate, our estimation of SCENS in Figure 9 is comparable with previous studies presented in Table 1.

In summary, we have investigated the interdependency effects and the economic impact of electricity supply interruptions. The most vulnerable sectors to power outage, in terms of inoperability and economic loss, were identified. The results of the study showed that inoperability does not necessarily correspond to a similar level of economic loss and these two metrics can differ in the case of power supply shocks. The results also showed that the ranking of sectors in terms of vulnerability to power supply disruption is robust in relation to the extent and duration of interruptions. We also computed the societal cost of energy not supplied (SCENS) given the interdependency among the infrastructure sectors and showed that SCENS strictly depends on the duration of interruption. The findings also indicated that SCENS starts from moderate values for very short duration of interruptions before increasing rapidly. Beyond a certain duration of interruptions, the SCENS converges to a specific range irrespective of initial inoperability level.

The results of this study provide some useful insights for policymakers and planners in their pursuit of improved electricity supply reliability and reductions in the economic impact of possible power outages. First, at sector level the regulatory incentives to reduce power interruptions need to justify investment in resiliency enhancement and quality of supply improvement. An estimation of the societal cost of power outage, which also takes into account the interdependency effects, can be used to calculate societal ‘willingness to invest’ in power quality, given the probability of outage. Overestimation or underestimation of the societal cost of power outage could lead to overinvestment or underinvestment, respectively, in power quality and security of electricity supply.

Second, at economy level, measures to protect critical assets need to be based on cost–benefit and risk analysis. There is always a trade-off between improving the resiliency of the power sector versus that of vulnerable infrastructures. An accurate analysis which compares the costs and benefits of resiliency improvements to the power sector with those of vulnerable sectors leads us towards an economically optimum level of reliability. Also, such analysis sheds light on the effectiveness of the available risk management measures such as reducing interdependency among critical infrastructures, increasing preparedness, and enabling smart response to major power cuts.

Third, the results highlight the need for an integrated security indicator which reflects several aspects of industry and business under extreme events. Such aspects would include: inoperability, economic loss, and the degree of importance of the sector for the welfare and well-being of the population. There is also a need for the development of relevant indices which measure the risk of different sources of failure, in addition to sector resilience and reliability. Theses indices could support managers and operators of critical infrastructures with tools enabling them to analyse and manage the risk holistically.

Finally, the results of this study provide useful insights for the management of outages and optimal operation of the power system. The ranking of vulnerable sectors based upon the *ex ante* analysis can help decision-makers address the issue of forced outage under extreme events in an economically informed way. Having developed indices that have sector level information about cost per MWh together with criticality of service for welfare and wellbeing, planners can avoid random outages in favour of commencing power rationing in the sectors at lower economic costs and inoperability levels.

Despite the appealing characteristics of the DIIM model, it has some limitations. First, an important assumption of the model is that the level of economic interdependency remains the same as the level of physical interdependency, and thus two sectors with high economic interdependency also have high physical interdependency (Haimes et al., 2005a). To the extent that economic interdependencies are obtained from multiplication of real physical interdependency and ‘undistorted producers’ prices’ this can be reasonable. This means that having an undistorted electricity price across an economy is crucial for this model, as this is a basic assumption of input–output tables. In the absence of real physical data (given that collecting such information is costly) on the interaction of sectors, the use of economic interdependency can be the second-best option for evaluating physical interdependency effects (Haimes et al., 2005a).

However, there are situations which may lead to underestimation or overestimation of the economic costs of power outage when using the DIIM approach. If the price of electricity is subsidised, or taxed differently in some sectors than others, this may lead to a distortion of outage costs, because it directly affects the strength of interdependency among them. Furthermore, there are some forms of losses which normally are not valued by DIIM and should be included separately, as in this paper. For example, the cost of lost leisure resulting from a power cut is not normally accounted for in input–output models; such costs should thus be evaluated separately. Additionally, DIIM may not calculate the restart cost of industries following interruption of production lines. Another form of loss which is not captured by this model is that caused by stock damage – for instance to items such as perishable goods and ticket sales (Théron and Bologna, 2013).

The second limitation is that the DIIM model strictly relies on the assumption of a Leontief coefficient matrix (A), hence all the limitations and assumptions in construction of this matrix apply to DIIM as well. Finally, the inoperability input–output model assumes an equilibrium condition in its static form (Haimes et al., 2005a).

This implies that the industries' inputs and outputs are in equilibrium with the final consumption. This assumption is true for the long-run analysis but can be violated after an inoperability shock and during the recovery period, if the initial inoperability level is assumed to be very high. In this situation, the recovery process does not reflect the actual behaviour of an economy under extreme events. However, if the initial inoperability shock is a fraction of total output (in other words, less than 100 per cent) then the results of the DIIM model are more reliable. This is because a partial inoperability within a large economy can be dealt with by redirection of resources from other parts of the economy during the recovery period.

5. Conclusions

The power sector is an industry on which many other infrastructures rely heavily. Hence, security of electricity supply has always been high on the agenda of policy makers and sector regulators. At the same time, many infrastructure sectors are interdependent and a failure in electricity supply will result in cascading effects, with consequences for the societal cost of energy not supplied (SCENS).

Therefore, it is imperative to understand the intricate interdependencies between the power sector and other infrastructures, together with the impact on other interdependent sectors when the electricity supply is perturbed. This study has analysed the interdependency effects and economic impact of electricity supply disruption using a DIIM model. We then applied the model to a case study of 101 sectors of the Scottish economy in 2009.

Our analysis demonstrated that inoperability can be different from economic loss and that highly inoperable industries in the short run (after shock) are not necessarily the same as those most affected economically. This is because the sensitivity of revenue and operational status to a particular input (for example, power) might vary for a given sector and across different sectors. The results also indicated that ranking of the affected sectors in terms of inoperability and economic loss metrics are robust with respect to extent and duration of interruptions. Based on an *ex ante* analysis and relevant data one can develop indices which has both information about economic cost (£/MWh) and criticality of service for society. This helps decision makers to prioritize vulnerable sectors for resource allocation and resiliency enhancement against major power outage incidences. It also helps to manage forced outages in an economically informed way by avoiding random outages.

We also estimated SCENS taking interdependencies among sectors of the economy into consideration. The results show that SCENS ranges from about £4300/MWh for 1 minute of interruption to a maximum figure of around £8100/MWh for an outage of three hours and more. Additionally, SCENS increases very marginally with the extent of power blackout (inoperability). The social cost of interruptions based on direct, indirect, and induced effects due to interdependency can be used to calculate 'societal willing to invest' in resiliency enhancement based on probability of power outages.

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Table A1: Industries of Scottish Economy used in Analysis (2009)

ID	Sector name	ID	Sector name	ID	Sector name
SE1	Agriculture	SE35	Other metals & casting	SE69	Information services
SE2	Forestry planting	SE36	Fabricated metal	SE70	Financial services
SE3	Forestry harvesting	SE37	Computers, electronics & opticals	SE71	Insurance & pensions
SE4	Fishing	SE38	Electrical equipment	SE72	Auxiliary financial services
SE5	Aquaculture	SE39	Machinery & equipment	SE73	Real estate – own
SE6	Coal & lignite	SE40	Motor Vehicles	SE74	Real estate – fee or contract
SE7	Other mining	SE41	Other transport equipment	SE75	Legal activities
SE8	Mining Support	SE42	Furniture	SE76	Accounting & tax services
SE9	Meat processing	SE43	Other manufacturing	SE77	Head office & consulting services
SE10	Fish & fruit processing	SE44	Repair & maintenance	SE78	Architectural services etc.
SE11	Dairy products, oils & fats processing	SE45	Electricity	SE79	Research & development
SE12	Grain milling & starch	SE46	Gas etc.	SE80	Advertising & market research
SE13	Bakery & farinaceous	SE47	Water and sewerage	SE81	Other professional services
SE14	Other food	SE48	Waste	SE82	Veterinary services
SE15	Animal feeds	SE49	Remediation & waste management	SE83	Rental and leasing services
SE16	Spirits & wines	SE50	Construction – buildings	SE84	Employment services
SE17	Beer & malt	SE51	Construction – civil engineering	SE85	Travel & related services
SE18	Soft Drinks	SE52	Construction – specialized	SE86	Security & investigation
SE19	Textiles	SE53	Wholesale & Retail – vehicles	SE87	Building & landscape services
SE20	Wearing apparel	SE54	Wholesale – excl. vehicles	SE88	Business support services
SE21	Leather goods	SE55	Retail – excl. vehicles	SE89	Public administration & defence
SE22	Wood and wood products	SE56	Rail transport	SE90	Education
SE23	Paper & paper products	SE57	Other land transport	SE91	Health
SE24	Printing and recording	SE58	Water transport	SE92	Residential care
SE25	Coke, petroleum & petrochemicals	SE59	Air transport	SE93	Social work
SE26	Paints, varnishes and inks etc.	SE60	Support services for transport	SE94	Creative services
SE27	Cleaning & toilet preparations	SE61	Post & courier	SE95	Cultural services
SE28	Other chemicals	SE62	Accommodation	SE96	Gambling
SE29	Inorganic chemicals, dyestuffs & agrochemicals	SE63	Food & beverage services	SE97	Sports & recreation
SE30	Pharmaceuticals	SE64	Publishing services	SE98	Membership organizations
SE31	Rubber & Plastic	SE65	Film video & TV etc.	SE99	Repairs – personal and household
SE32	Cement lime & plaster	SE66	Broadcasting	SE100	Other personal services
SE33	Glass, clay & stone etc.	SE67	Telecommunications	SE101	Households
SE34	Iron & Steel	SE68	Computer services		